Improving the applicability of radar rainfall estimates for urban hydrological applications through gauge-based adjustment

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Workshop - Improving rainfall estimation for water industry use by merging radar and raingauge data: A UK-wide strategy

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We have explored two aspects of radar (RD) – raingauge (RG) merging:

1. Improvement of radar QPEs
   (to be used for estimation of urban runoff)

2. Improvement of radar-based nowcasts (short-term QPFs)
   which take as starting point merged QPEs
   (to be used for short-term forecasting of storms and associated urban runoff)
INVESTIGATION OF RG/RADAR MERGING FOR IMPROVING QPEs AND ASSOCIATED URBAN RUNOFF ESTIMATES

For more details:
GENERAL METHODOLOGY

Different Rainfall Inputs

Original raingauge (RG)

Interpolated raingauge (BK)

Original Radar (RD)

4 Merged rainfall products

Performance Assessment
NSE, Correlation, Relative Error in peaks

Urban drainage models

Cranbrook, London

Portobello & WofL, Edinburgh

SW Birmingham

Simulated and recorded flow depth: Storm 1 - Gauging station 1

Obs RG RD BK MFB BAY SIN
1. Mean Field Bias (MFB) adjustment:
   - Mean raingauge rainfall records over a specific area are assumed to be truth and able to represent the areal rainfall volume: $Bias_{last \ 1h} = \frac{\sum RG}{\sum RD}$

2. Kriging with External Drift (KED):
   - Simple method to include radar rainfall estimates in the raingauge interpolation process.
   - This is done by constraining the weighting factor $(\lambda_{i}^{KED})$ with the spatial association between radar values.
3. Bayesian (BAY) adjustment: (Todini, 2001)

- Neither radar nor raingauge estimates are fully trusted

- Main idea: analyse the uncertainty of rainfall estimates from different sources (in this case radar and raingauge sensors) and combine them such that the overall uncertainty is minimised
Principle of Bayesian Data Combination

[Block-Kriging interpolation]

RG data

a)

b)

Block-Kriging interpolation

c)

d)

Combination (Kalman filter)

e)

f)

g)

[Radar data]

Radar data

comparison

error field fitting (using exponential variogram)

In this process the variance of the error is minimised

[Image : Ehret et al., 2008]
[Source: Todini, 2001]
3. Singularity-Sensitive Bayesian (SIN) adjustment: (Wang et al., 2014)

- Recently developed to overcome a shortcoming of the original Bayesian (BAY), which tend to smooth storm extremes initially observed in radar images.

- This method identifies **local extremes** (i.e. **singular points**) and extracts them from the radar image before the merging takes place. After the merging is finished, the singularities are applied back and proportionally to the rainfall field.
TEST CATCHMENTS

SW Birmingham
67 km²
20 RG, 41 flow/depth gauges

Portobello, E Edinburgh
53 km²
12 RG, 32 flow/depth gauges

Water of Leith, E Edinburgh
93 km²
16 RG, 67 depth gauge

Cranbrook, NE London
9 km²
3 RG, 1 depth gauge
### Areal average total rainfall accumulations

<table>
<thead>
<tr>
<th>Rainfall Estimates</th>
<th>Storm 1</th>
<th>Storm 2</th>
<th>Storm 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>RG</td>
<td>9.25</td>
<td>7.70</td>
<td>32.96</td>
</tr>
<tr>
<td>RD</td>
<td>9.67</td>
<td>10.80</td>
<td>25.85</td>
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<tr>
<td>BK</td>
<td>9.02</td>
<td>7.50</td>
<td>30.69</td>
</tr>
<tr>
<td>MFB</td>
<td>8.47</td>
<td>7.13</td>
<td>31.94</td>
</tr>
<tr>
<td>KED</td>
<td>9.38</td>
<td>7.79</td>
<td>32.77</td>
</tr>
<tr>
<td>BAY</td>
<td>8.80</td>
<td>7.51</td>
<td>26.94</td>
</tr>
<tr>
<td>SIN</td>
<td>9.66</td>
<td>7.56</td>
<td>33.73</td>
</tr>
</tbody>
</table>

### Areal average RG rain rates VS. areal average rain rates of radar and merged estimates

- All adjustment methods can, in general, reduce RG/RD cumulative bias, leading to areal total accumulations similar to those recorded by raingauges.
- But: not all methods can effectively correct instantaneous rainfall rates (SIN performs particularly well at this)!
PORTOBELLO CATCHMENT: Observed vs. Simulated flow depth and rate at up-stream gauging station

- In spite of small RG/RD bias, RD underestimates peaks
- MFB not enough
- BAY ok
- KED very similar to RG
- SIN better at capturing peak
PORTOBELLO CATCHMENT: Observed vs. Simulated flow depth and rate at mid-stream gauging station

- In spite of small RG/RD bias, RD underestimates peaks
- MFB not enough
- BAY and SIN perform well
PORTOBELLO CATCHMENT: Observed vs. Simulated flow depth and rate at **down-stream** gauging station

- RD underestimates even more (cumulative effect?)
- MFB not enough
- RG overestimates peak, KED cannot correct this
- Even BK performs better than RG
- BAY and SIN perform well
Portobello catchment – Images at peak intensity (Storm 1)

- RD
- BK
  - Simple interpolation, very smooth
- MFB
  - Simple scaling of RD
- KED
  - Looks rather similar to simple BK interpolation
- BAY
  - Seems to incorporate more elements of RD than KED. Highly smooth
- SIN
  - Seems to incorporate more elements of RD, shows more realistic spatial structure
Conclusions:

• In general, **all adjustment methods improve the applicability of the original RD rainfall estimates** to urban hydrological applications, but degree of improvement varies for each method.

• **Simple MFB is insufficient** for satisfactorily correcting the errors in RD estimates and this is evident in the associated hydraulic outputs - more dynamic and spatially varying adjustment methods are required for urban hydrological applications.

• **KED estimates lead to goo results, very similar to original RG ones** (the influence of RD is not very evident)

• Overall, **the BAY and SIN rainfall estimates produce best performance**, with the **SIN estimates performing particularly well at reproducing peak depths and flows**.
Future work (modelling context)

- Still need to ‘polish’ analysis of results

- Analyse impact of raingauge density. The benefits of the merging, particularly BAY and SIN methods, are likely to become more evident when fewer gauges are available!

- Incorporate uncertainty in RG and RD measurements in the merging process (this can be done in the Bayesian approaches)

- Testing other merging methods?
INVESTIGATION OF RG/RADAR MERGING FOR IMPROVING RADAR-BASED NOWCASTS (QPFs) AND SHORT-TERM PREDICTION OF URBAN RUNOFF

For more details:
Radar (Nimrod) and raingauge measurements (domain: 500 km x 500 km)

Gauge-based adjustment: Mean field bias & KED

Generation of QPFs with STEPS Nowcasting model

Runoff forecasts – inputting QPFs to InfoWorks model of Cranbrook catchment

Assessment of QPEs, QPFs and runoff forecasts using Cranbrook local raingauge and depth sensors

Cranbrook, NE London
9 km²
3 RG, 1 depth gauge
QPE assessment at urban scale

- Radar largely underestimate rainfall over the Cranbrook area (this seems to be due to radar beam blocking)
- Adjustments were done at too large scales and no improvements were achieved at the local scale of urban catchments
- Need to apply adjustment (both mean bias and KED) at smaller domains – our previous work supports this statement
QPF assessment at urban scale

- **Quantitatively:** all QPFs perform badly – mainly due to underestimation of QPEs

- **In terms of correlation and storm movement:**
  - Nimrod and bias adjusted QPFs present consistent behaviour
  - KED QPFs present inconsistent behaviour, the storm even changes direction – reason: KED adjustment does not take into account the temporal correlation of the radar rainfall field; therefore, the adjustment affects the rain field in the time domain. Consequently, the nowcasting model is not able to properly capture the movement of the storm
Runoff forecast assessment at urban scale

- Quantitatively: better results (than QPFs alone)

- In terms of correlation and consistency:
  - Nimrod and bias adjusted QPFs present consistent behaviour
  - KED QPFs present inconsistent behaviour

GENERAL CONCLUSIONS

- Need to apply adjustment at smaller domains (need to investigate optimal scale)

- Preserving temporal correlation of rainfall fields is essential if estimates are to be used for nowcasting applications (in this respect, KED QPEs do not seem suitable for generating QPFs)
THANK YOU

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Why we need to adjust radar rainfall data?

Beal HS raingauge rainfall depth accumulations: 23/08/2010 event

Urban drainage models are normally calibrated using raingauge data
Problem posed by one of our observers following last year’s NOG meeting:
- Reconstruction of a historical (2009) storm event that caused flooding in a sector of London
- Radar estimates showed storm cell, but seemed to underestimate intensities
- No RG data available within the area of interest

What we did:

• Gathered RG data from multiple and often under-utilised sources

• Realised that the techniques we had tested tend to smooth-out rainfall extremes, especially when there are no RGs in the areas of extreme precipitation

• Developed a new technique which allows identifying and better preserving rainfall extreme patterns through the merging process
New technique: singularity analysis for better capturing and preserving storm extremes through the merging process.
Integration of local singularity analysis

- Block-Kriging interpolation
  - BK rain gauge field

- Singularity extraction
  - Non-Singular (NS) radar field

- Comparison (error field construction)

- Error field fitting

- Combination (Kalman filter)

- Reconstruction of field
Images at each step of the Bayesian data merging with/without local singularity analysis

Nimrod (Original) → Block-Kriged RGs → Bayesian Merged
Non-singular Radar → Non-singular Merged → Singularity-Sensitive Merged

Singularity Back